

Review

Estimating the Aboveground Biomass of Shrubland and Savanna Ecosystems Using High-Resolution Small UAV Systems: A Systematic Review

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Highlights

What are the main findings?

- Tundra vegetation, as well as shrubs, half-shrubs, and low-stature trees (<2 m height), in drylands are the least studied lifeforms in the selected remote sensing literature.
- Incorporation of spectral and structural predictors did not improve aboveground biomass model performance within the reviewed studies ($n = 50$) compared to the use of spectral or structural predictors alone.

What are the implications of the main findings?

- As species and structural diversity increase within shrubland or savanna systems, species-specific allometric equations and more complex UAV remote sensing data captures (LiDAR, hyperspectral, multispectral, and RGB) may be necessary to estimate aboveground biomass within REDD+ standards with <10% uncertainty.
- Increased research investments should be made into development of allometric models for shrubs and multi-branching tree species based on variables that can be estimated with UAV-mounted sensors and associated models.

Abstract

Global biomass estimates suggest that plants hold 81% of the Earth's 550 GT C, yet carbon stocks in non-forested and dryland ecosystems remain the largest source of uncertainty in the global carbon budget. Small uncrewed aerial vehicle (UAV) platforms are increasingly used to estimate aboveground biomass at landscape scales. We conducted a systematic review of the remote sensing literature to determine: (1) which plant traits and related remote sensing indicators were used to develop aboveground biomass models; (2) statistical approaches; and (3) the key sources of uncertainty among these methods and models. We found that tundra, dryland, and savanna ecosystems were most underrepresented in the remote sensing literature. Within our systematic review process, we found no consistent UAV sensor combination, platform, or workflow that improved the accuracy and reduced the uncertainty in aboveground biomass estimates. Machine learning and regression models resulted in similar uncertainty levels in shrubland and savanna ecosystems. Expanding



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allometric equation development in shrublands and savanna ecosystems could reduce uncertainty and improve aboveground biomass estimation. Improved reporting on UAV logistics and workflows would further strengthen comparability. Standardized and validated UAV methods for estimating biomass, carbon stocks, and fuel loads will be essential for producing consistent datasets and enabling robust future meta-analyses.

Keywords: aboveground biomass; carbon stocks; remote sensing; shrublands; uncrewed aerial vehicles; unmanned aerial systems; UAV

1. Introduction

Plants encompass approximately 80% (about 450 Gt C) of the total biomass across all taxa on Earth [1]. Vegetation biomass or phytomass is most simply quantified by weighing the whole plant by scale or by mass balance approaches using a lysimeter. Phytomass is the total wet and/or dry weight of photosynthetic and non-photosynthetic plant material, including above- and belowground portions [2]. It can be defined using a number of synonyms, including dry and wet forage, standing crop, production, gross and net primary productivity, fuel loads, and mass fractions. Estimation of aboveground biomass, or photosynthetic plant mass [2], is an important ecosystem metric for tracking landscape changes over time, quantifying fuel load accumulation, reporting efforts toward carbon sequestration, and monitoring anthropogenic activities such as livestock grazing [3,4]. Drylands, as defined by an aridity index ≤ 0.65 , are estimated to cover 41% of the Earth's land surface area and provide \$18.4 trillion in ecosystem services [5] that support the livelihoods of over 2 billion humans each year [6]. Within drylands, shrublands and savanna ecosystems are estimated to cover 13% and 11%, respectively [7]. Additionally, barren areas (<10% vegetation cover), which cover 27% of all drylands, also support shrubland vegetation [7]. Through the use of high-resolution satellite data, estimates of global land surface area covered by shrublands, savannas, and barrens are in temporal flux [7]. Dryland shrub, savanna, and barren lands are considered important carbon stores [8].

Drylands have been considered the least productive ecosystem types, leading Ludwig [9] to call this perception a myth due to the heterogeneous distribution of sparsely concentrated vegetation patches and large bare ground patches in drylands. The division of this total land area into the productivity of vegetation patches yields low per unit area production estimates in drylands. However, when productivity is estimated solely in dryland vegetation patches, it is comparable to other ecosystems, particularly forests [9,10]. This knowledge gap has led to surprises, such as drylands being the largest carbon sink in the world [11]. U.S. drylands are estimated to store 0.13 Pg C/yr, but this land type is considered the least secure storage source in the land-based carbon budget [12,13]. Drylands, particularly shrubland, savanna, and barren lands, may be important carbon stores [8], yet there is a large knowledge gap and uncertainty in estimates of above- and belowground biomass [8,9,14] and in spatial variability [15].

Surface area estimates of dryland ecosystems are known to be in flux, with some areas increasing in greenness over the last three decades, while other dryland areas in the southwestern United States, Kazakhstan, Mongolia, Afghanistan, and dryland regions of Australia have declined in vegetation cover [6]. While precipitation patterns and aridity are major drivers of vegetation productivity [6,7,16], the effects of those drivers can be challenging to observe at ecologically relevant scales through satellite-based remote sensing approaches, especially when shrub or tree density is sparse, or when the growing season is

quite short. Impacts such as early stages of shrub encroachment, early stages of annual grass invasion, small tree (≤ 2 m height) and shrub mortality of species that only leaf out for short durations or are very sparsely distributed, and other shifts in plant community composition may be detected and managed more appropriately if captured at higher temporal and spatial resolution than most freely available satellite-based sources provide [6,16].

Active and passive sensors mounted on uncrewed aerial vehicles (UAVs) have been proposed as a high-resolution remote sensing solution for studying plant community dynamics, monitoring vegetation [17], and evaluating early subtle changes over time in dryland vegetation cover, fine fuel accumulations, and aboveground biomass [18–20]. The UAV platforms and sensors that are recently available allow researchers to study vegetation at spatial scales in the range of (<1 mm to 50 cm), and those at 50 cm spatial resolution are just becoming available through civilian-grade satellite systems. Other systematic reviews have demonstrated the utility of active sensors, like light detection and ranging (LiDAR), and passive optical sensors, such as multispectral cameras or other UAV-mounted spectral sensors for studying forests [21–24], grasslands [17,18,25] and cropland systems [18,26,27]. The aforementioned reviews provide detailed descriptions of the use of UAV-mounted systems for the estimation of aboveground biomass in these ecosystems, but they do not reflect the physiognomic structure, data acquisition methods, and model development procedures that are specific to shrublands and shrubs in other ecosystems, particularly savanna ecosystems [16]. Consequently, few studies appear to exist on estimates of aboveground biomass at the high spatial resolution provided by UAV-mounted sensors for shrubs in shrubland and savanna ecosystems, especially for conducting carbon inventories and determining fuel load contributions to the risk of wildfire.

The two primary research objectives of this review were to: (1) determine if underrepresentation of shrubland and savanna systems exists in the remote sensing literature, and if so, to what extent, and (2) systematically examine the UAV literature to distill and describe the most common methods and techniques used for estimating aboveground biomass of shrubland and savanna ecosystems. Since dryland shrub and savanna systems can be important for net carbon uptake [8,10], for domestic livestock and wildlife forage and browse, for wildlife shelter, and for human foraging of firewood and charcoal production, medicines, diets, and construction material [28], this review seeks to enumerate the work completed and emerging in shrubland and savanna systems. This opus will also provide the first systematic literature review for the use of UAV-mounted sensors for the estimation of the aboveground biomass of the world's shrublands and savannas. The goals of the systematic literature review are: (1) determine the most prevalent methodologies used for estimating aboveground biomass in these shrubland and savanna systems; (2) summarize the most common UAV mission-planning parameters used, including sensor types, ground truthing methods, and data processing strategies; (3) evaluate the efficacy of the methodologies for aboveground biomass estimation; and (4) identify research gaps.

2. The Case for Estimating Aboveground Biomass in Shrublands and Savannas

Within this paper, we have adopted the broad definition of “shrub”, as provided by Conti et al. [29], referring to woody non-climbing plants with multiple stems, not having a single main stem with clear apical dominance. Other than directly weighing shrub species in the field, non-destructive estimates of aboveground biomass using remote sensing require the development of allometric equations. While Conti et al. [29], Paul et al. [30], and Jucker et al. [31] have all proposed versions of a universal shrub biomass allometry model, each failed to consistently meet the United Nations Framework Convention on

Climate Change (UNFCCC) REDD+ (Reduced Emissions from Deforestation and Forest Degradation plus role of forest management for the enhancement of carbon stocks) standards of less than 10% uncertainty in biomass estimates. Alternatively, shrubland biomass estimates involve field measurements of height, crown area or cover, crown widths, basal stem diameter, or other predictor variables to develop species- or genus-specific allometric models. Destructive sampling is necessary to develop accurate allometric models. Shrubs are much more challenging than grasses to destructively harvest, dry, and weigh due to their increased size and longer drying times. For important shrub species in the Great Basin region where the authors live, several published allometric equations have been developed with fewer than 40 harvested individuals [32–35]. Roxburgh et al. [36] recommended a minimum of 50–60 individuals for the development of satisfactory allometric equations. Adding to the challenge of biomass estimation for shrubs, early researchers did not develop allometries with the view of future remote sensing capabilities in mind. UAV-based platforms and other remote sensing tools usually cannot directly measure the stem diameter of most shrub species due to canopy occlusion. Consistent with allometry theory or biological scaling, the study of body size to shape [37–40], researchers are in the process of developing models that scale shrub structural traits that can be measured with remote sensing to direct measurements of shrub biomass.

Timber harvest or other extractive tree resources (syrup, latex, etc.) have driven research into the estimation of aboveground biomass or phytomass in trees to better predict resource availability and profitability of various extraction techniques (e.g., clear-cutting, group selection, thinning). Trees are measured differently in the field than shrubs or grasses due to their different physiognomic structures [29,41]. Standard field methods involve collecting information on tree height and canopies, and sometimes canopy widths, using poles, clinometers, or laser range finders. The tree bole is measured by collecting the diameter at breast height (DBH) or 1.3 m above ground level [41,42]. These characteristics are then combined with destructive sampling to develop allometric equations that estimate aboveground biomass and/or carbon stocks [41]. Smaller trees or trees that branch repeatedly closer to the ground than 1.3 m are sometimes measured at 10 cm above ground level and equilibrated from multiple stem measurements [30]. Unlike temperate tree species used for timber, tropical and dryland tree species often lack species-specific allometric models, making aboveground biomass estimation more difficult in tropical savannas [41].

Several ecosystem characteristics of shrublands and savannas require different approaches to remote sensing studies as opposed to grasslands and temperate forests. Differences include the absence of a consistent overstory tree canopy matrix, the physiognomic diversity of plants, and fire frequency, all of which cause shifts in plant community dynamics among grasses, shrubs, small trees, and large trees across space and time. UAV-based methodologies developed for the study of agricultural crops, grasslands, and forests are often inappropriate for studying dynamic shrubland and savanna systems without testing their suitability in these highly heterogeneous systems.

3. Systematic Review and Assessment Methods

3.1. Remote Sensing Literature Assessment Methods

To address research objective 1, we conducted a literature search in a selection of four of the major English-language remote sensing journals between 1996 and 2022. To obtain a representative sample of ecosystem prevalence in the peer-reviewed literature, four journals were selected for sampling: *Remote Sensing*, *Remote Sensing of the Environment*, *Photogrammetric Engineering & Remote Sensing (ISPRS)*, and the *International Journal of Remote Sensing*. A total of 36 search terms were applied independently to each journal to record the number of articles contained within a journal containing each term. The number and

variety of search terms were not developed systematically and resulted in unequal numbers of search terms for each ecosystem type. The number of articles returned was recorded for each term and for each journal (Table 1). The search was conducted on 17 May 2022.

Table 1. List of 34 search terms used and their landscape grouping for conducting the search of the breadth of the remote sensing literature in English-language journals.

Ecosystem Group	Search Terms
Drylands	Dryland, Rangeland, Desert
Grasslands	Grassland, Pasture, Plains, Prairie
Savannas	Savanna, Woodland
Tundra	Tundra, Arctic, Antarctic, Alpine, Glacial, Glacier, Ice, Snow
Forests	Fores, Boreal, Mountain
Wetland	Wetland, Riparian, Ocean, Oceanic, Lake, Pelagic, Reef, Coastal, River, Aquatic
Farmland	Crop, Cropland
Urban	Urban, Suburban
Atmosphere	Atmosphere, Atmospheric

3.2. Systematic Literature Review Methods

For the second research objective (systematic literature review), four academic databases (Web of Science, Academic Search Premier, ScienceDirect and SpringerLinkNature) were used to identify peer-reviewed papers using a different set of search terms than those used to complete research objective 1 (Table 2). Additional papers were identified using identical search parameters entered into Google Scholar and Connected Papers. The 2020 updated Preferred Reporting Items for Systematic reviews and Meta-Analyses (PRISMA) protocol was used to carry out the procedures in the review and reduce bias in the outcomes (Figure 1) [43]. We limited the search to English-language articles with no limitation on publication date. The review was restricted to peer-reviewed articles and excluded abstracts, conference proceedings, case reports, book chapters, reports, reviews, theses, and dissertations. The Academic Search Premier database search tool did not allow all Boolean operators to be used in the search. Instead, articles that contained any of the search terms listed in Table 2 were returned through Academic Search Premier. Figure 1 details the number of articles returned from each database.

Table 2. Boolean search terms used for article search within academic databases.

Search Categories	Search Terms
Technology	"UAS"OR "UAV" OR "sUAS" OR "drone" OR "unmanned aerial system" OR "unmanned aerial vehicle" OR "uncrewed aerial system" OR "uncrewed aerial vehicle"
Ecosystem	AND "brush" OR "shrub" OR "chamise" OR "chaparral" OR "savanna" OR "shrubland" OR "heath" OR "heather" OR "sparse woodlands" OR "steppe"
Characteristic	AND "aboveground biomass" OR "AGB" OR "productivity" OR "production" OR "annual production" OR "standing crop" OR "biomass"

Filtering of articles was conducted based on exclusion criteria that included: (1) articles that did not address UAV and biomass estimation and shrubland or shrub–savanna ecosystems and (2) articles about forests and savannas that only measured large trees (>10 cm diameter at breast height (DBH), and/or only trees taller than 5 m) and did not consider understory shrub vegetation or small trees < 5 m were excluded. The exclusion criteria were applied in two steps through manual review by two independent reviewers: In Step (1),

titles, keywords, and abstracts were reviewed for required search terms. In Step (2), article method and result sections were reviewed to confirm exclusion criteria for articles that were unclearly described in article sections reviewed during Step 1. To reduce bias and error, one reviewer conducted searches across each of the databases for the keyword search described above. To reduce the likelihood of bias in the application of the exclusion criteria, two independent reviewers screened each paper according to the exclusion criteria and then corrected any discrepancies found following their independent reviews. A review of Google Scholar and Connected Papers was performed to search for any articles that met the inclusion criteria but were not identified through the academic database search engines. The article search procedure was completed between 18 November 2024 and 26 November 2024. Articles published after October 2024 were not included in the review.

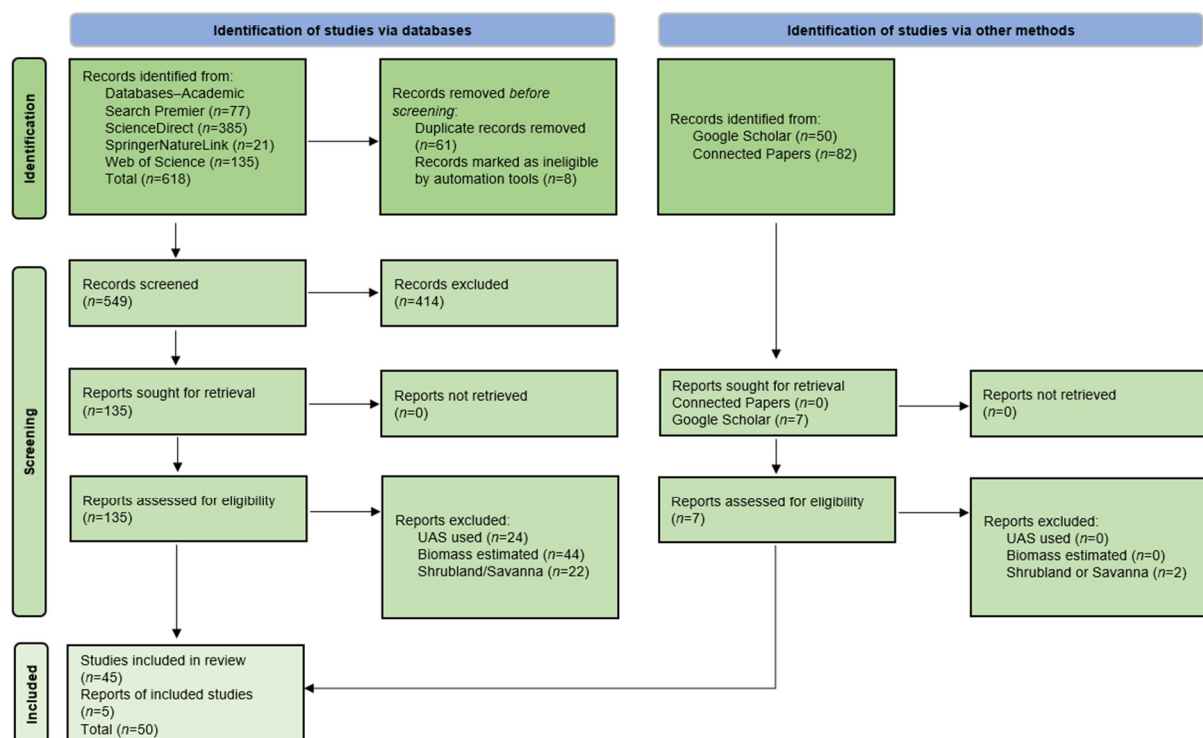


Figure 1. PRISMA [43] flow diagram for systematic reviews for UAV studies on shrub and savanna aboveground biomass estimation.

3.3. Data Analysis

All data analyses and figures were completed using R version 4.4.2 [44]. A beta regression model using the “betareg” package in R was used to fit a model to evaluate the effect that the number of search terms used had on the percentage of the literature covered under each ecosystem group. Standardized residuals were examined, and each ecosystem group was re-ranked after removing the effect of the number of search terms used on the percentage of the literature about each group. Within the systematic literature review, coefficients of determination were recorded for the best-performing model from each paper. After data visualization and examination revealed that normality and homoscedasticity assumptions were met, we performed a one-way ANOVA using the R “stats” package and reviewed Tukey HSD pairwise comparisons using the “car” package to examine effects of data collection class (structural, spectral, or structural and spectral) on model performance [45]. We used ordinary least squares (OLS) regression to examine the effect of model type (machine learning or regression) on model performance.

4. Results

4.1. Ecosystem Representation in the Remote Sensing Literature

To address the first research objective of this paper, the results of a number of ecosystems are presented in Table 3. Quantitatively, dryland ecosystems and savannas were the two least-represented ecosystem types in the sample of the peer-reviewed literature from the four remote sensing journals. The beta regression model revealed a significant positive association between the quantity of search terms used and the percentage of articles retrieved (pseudo $R^2 = 0.43$; p -value = 0.0006). When evaluating the standardized residuals for each ecosystem group, tundra was the least studied ecosystem group, followed closely by drylands and savannas. Atmosphere and wetlands were the most represented ecosystem groups in the literature searched in terms of both the total percent of articles identified in the sample and the standardized residual rank. The journal *Remote Sensing* represented the largest proportion of articles identified, while *ISPRS Photogrammetric Engineering & Remote Sensing* represented the smallest proportion. These results are representative of the 2022 impact factors of these two journals, estimated at 5.39 and 0.96, respectively.

Table 3. Summary of remote sensing journal search results for articles available within the date range 1996–2022 by ecosystem type or land use type. Numerical percentages of articles per group from the overall total of 197,398 articles are reported. Ranking of representation in the literature was determined by the standardized residuals of a beta distribution regression model, which corrected for variations in the quantity of search terms used for each group.

Search Terms	Remote Sensing	Remote Sensing of Environment	Photogrammetric Engineering & Remote Sensing	International Journal of Remote Sensing	Total # of Articles	% of Articles	% of Articles by Group	Standardized Residual Rank
Drylands	726	74	25	86	911	0.5	2.8	8
Rangeland	743	108	106	196	1153	0.6		
Desert	2495	271	139	571	3476	1.8		
Grassland	3747	397	223	710	5077	2.6	6.5	6
Pasture	1341	90	130	335	1896	1.0		
Plains	3845	202	214	680	4941	2.5		
Prairie	564	120	57	118	859	0.4		
Savanna	1566	221	97	317	2201	1.1	2.1	7
Woodland	1388	127	136	330	1981	1.0		
Tundra	642	128	19	100	889	0.5	10.4	9
Arctic	1756	383	50	280	2469	1.3		
Antarctic	772	131	31	202	1136	0.6		
Alpine	1500	112	67	184	1863	0.9		
Snow	4212	778	172	619	5781	2.9		
Ice	4032	683	156	614	5485	2.8		
Glacial	865	106	51	94	1116	0.6		
Glacier	1342	250	63	137	1792	0.9		
Forest	9898	2980	900	1899	15,677	7.9	12.9	3
Boreal	2037	600	118	381	3136	1.6		
Mountain	4886	490	459	836	6671	3.4		
Wetland	2946	374	257	456	4033	2.0	36.9	2
Riparian	650	58	89	144	941	0.5		
Ocean	6301	5452	1212	3930	16,895	8.6		
Oceanic	2882	830	119	1191	5022	2.5		
Lake	4688	603	477	805	6573	3.3		
Pelagic	139	34	2	42	217	0.1		
Reef	532	92	46	92	762	0.4		
Coastal	5264	823	380	1005	7472	3.8		
River	7303	708	633	1364	10,008	5.1		
Aquatic	17,904	2076	131	899	21,010	10.6		
Crop	5842	691	392	1072	7997	4.1	5.6	5
Cropland	2495	215	126	291	3127	1.6		
Urban	7766	813	878	1181	10,638	5.5	5.8	4
Suburban	606	35	126	140	907	0.5		

Table 3. Cont.

Search Terms	Remote Sensing	Remote Sensing of Environment	Photogrammetric Engineering & Remote Sensing	International Journal of Remote Sensing	Total # of Articles	% of Articles	% of Articles by Group	Standardized Residual Rank
Atmosphere	6815	1091	255	1743	9904	5.0		
Atmospheric	18,362	1945	526	2549	23,382	11.8	16.9	1
Total Articles	138,852	24,091	8862	25,593	197,398			

4.2. Results of Systematic Literature Review

The search process was followed according to the procedures displayed in the PRISMA diagram (Figure 1). The ScienceDirect database yielded the greatest number of potential articles ($n = 385$), with Web of Science ($n = 135$) yielding the next greatest. In total, 618 articles were initially identified for screening before duplicates and article filters were applied. The filtering process reduced the number of articles to 135 from databases and seven from Google Scholar. After a detailed review, 50 articles met the full search criteria. The agreement between the two independent reviewers was high, with 42 of the 50 papers included identified as meeting the search criteria.

4.2.1. Description of Reviewed Papers

Studies in China represented the greatest portion of the geographical locations of the research trials ($n = 14$), and the United States was next ($n = 12$) (Figure 2). These two countries represented over 50% of the research included. Study site locations represented every continent except Antarctica, demonstrating a wide sample of global shrubland and savanna ecosystems. The domestic comprehensive wealth index of the 19 countries represented in the selected papers was 4.7 times greater than that of the 151 countries included in the 2020 World Bank dataset [46]. However, the standard deviation of the countries included in this review was 2.6 times greater than that of the 151 countries in the dataset, indicating that UAV-based research has included a diverse representation of countries. On average, wealthier nations use drones in research, but not as a rule.

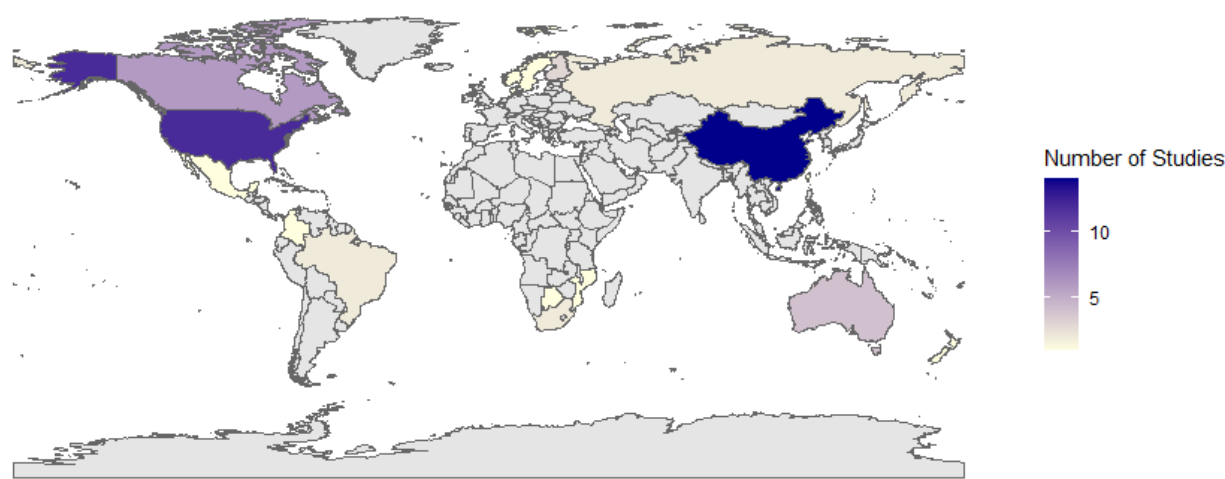


Figure 2. Global distribution of peer-reviewed studies using uncrewed aerial vehicles (UAVs) for developing models of aboveground biomass in shrubland and savanna ecosystems, or of plant species similar in size and growth form to shrubland and savanna plants ($n = 48$, two global studies not represented).

The span of publication years represented was 2014–2024, with the greatest number of papers ($n = 13$) published in 2022 (Figure 3). Across the papers evaluated, 415 authors participated in the research, and of those, 380 were unique authors, meaning they were

not repeated in other papers within our review. Twenty-four different journals published these studies. The journals *Remote Sensing of Environment* and *Remote Sensing* were the top two publications ($n = 8$ each), while the *International Journal of Applied Earth Observation and Geoinformation* and *Environmental Research Letters* followed with five and three publications, respectively. The keywords used across titles and abstracts revealed the preferences of researchers for the reference of drones as unmanned aerial vehicles and were abbreviated as UAVs (Table 4). This naming preference was used approximately six times more often than other synonyms found across the 2356 unique words in the titles. Due to recent journal trends asking authors to remove gendered terms from submissions, we looked at the dates of publication for articles that used ungendered terms. Eight articles used ungendered terms such as uncrewed, unpiloted, or unoccupied. Of these eight, one was published in 2016, one in 2020, two in 2022, one in 2023, and three in 2024. *Remote Sensing of Environment* and *Remote Sensing in Ecology and Conservation* were the publishers of six of the eight articles that used ungendered terms for UAVs. The most frequently used words within the titles and abstracts of the included articles are represented in Figure 4. The word frequency patterns revealed that carbon estimation, fuel, and fire concerns were the most pressing reasons why researchers estimated aboveground biomass in the shrubland or savanna vegetation types they were working in.

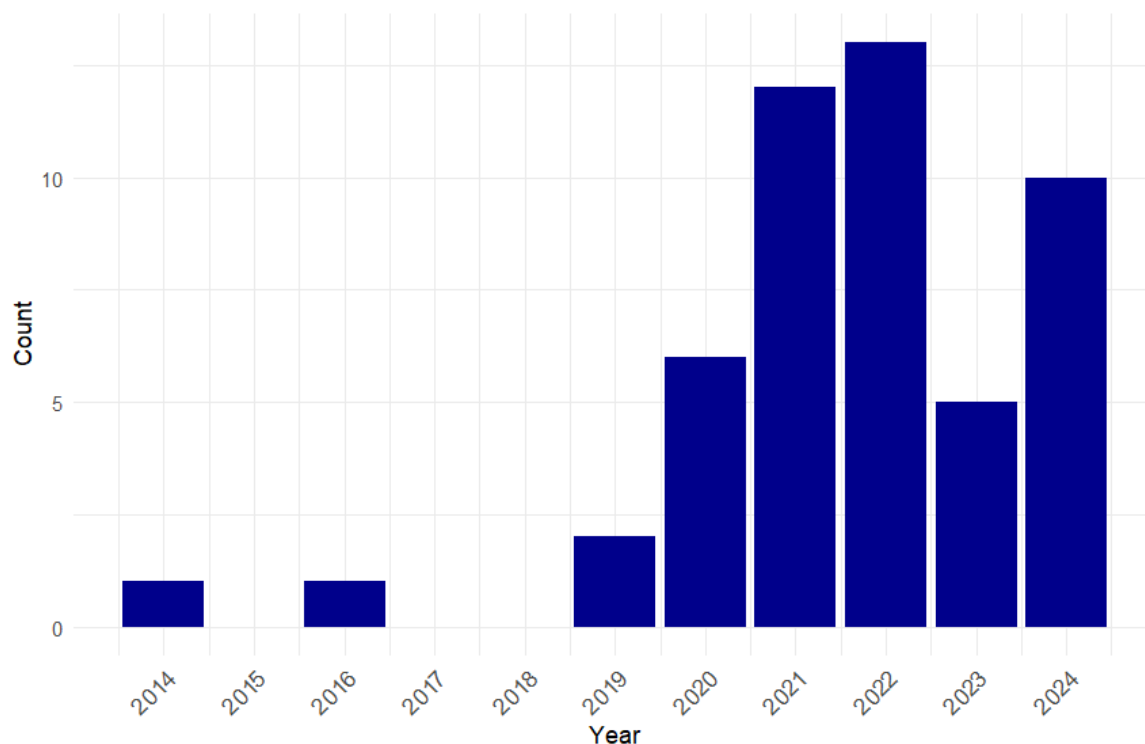


Figure 3. Range and number of publications by date of peer-reviewed studies using uncrewed aerial vehicles (UAVs) for developing models of aboveground biomass in shrubland and savanna ecosystems ($n = 50$).

We attempted to group the vegetation types described for each study site in the reviewed papers, yet we found that it was difficult to select a single classification system that would cover the various study site descriptions (Table 5). Two of the reviewed papers were global in extent, covered many different ecoregions, and were thus sorted into their own global category, with 4 and 36 study sites each [47,48]. Orndahl et al. [49,50] estimated regional biomass across Canada and Alaska in boreal forest, wet tundra, shrubland, and

lichen barrens across 44 study sites. All other research papers reported between one and four study sites used for their research (Table S1).

Table 4. Title and abstract drone-based terminology for small unoccupied aerial systems ($n = 2356$ words).

Drone System Terms	Number of Usages
UAS	24
sUAS	0
UAV(s)	147
Drone(s)	18
unpiloted	1
unmanned	41
unoccupied	6
uncrewed	3

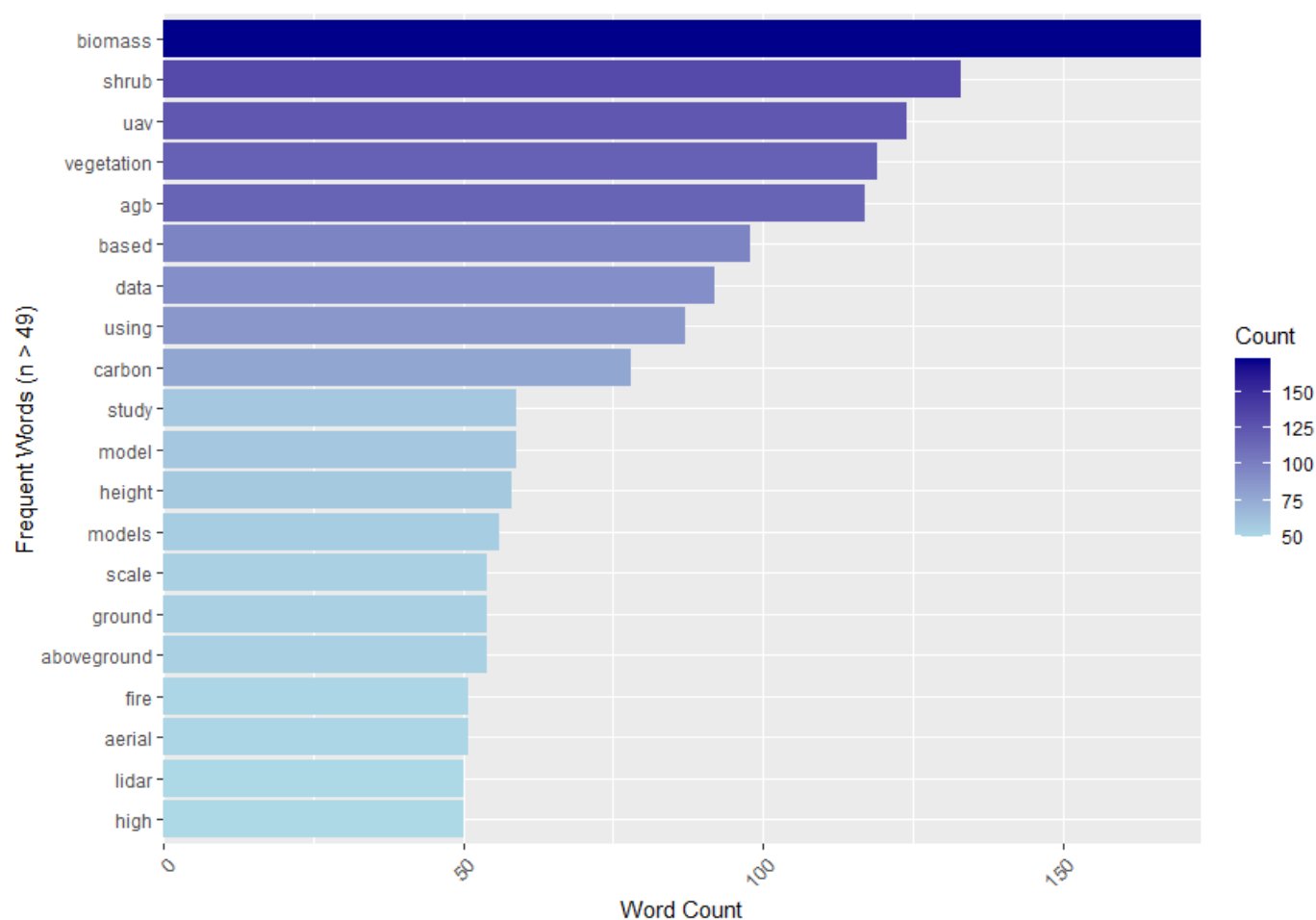


Figure 4. Most used words and their total count in the titles and abstracts of the 50 papers included in the systematic literature review on uncrewed aerial vehicle (UAV) aided biomass estimation in shrubland and savanna ecosystems.

Table 5. Summary of shrubland and savanna vegetation types described within the 50 identified papers following the PRISMA systematic literature review process.

Vegetation Type	Authors
Deserts or Xeric Grassland/Shrubland	Abdullah et al. [51], Abdullah et al. [52], Cunliffe et al. [53], Ding et al. [54], Liu et al. [55], Mao et al. [56], Mao et al. [57], Mao et al. [58], Sankey et al. [59], Sun et al. [60], Vega-Puga et al. [61], Zhao et al. [62], Zi-chen et al. [63]
Tropical and Subtropical Grasslands/Savannas/Shrublands	Eames et al. [64], Leite et al. [65], Levick et al. [66], Matyukira and Mhangara [67], McCann et al. [68], Pan et al. [69], Sagang et al. [70], Singh et al. [71], Teixeira da Costa et al. [72]
Arctic/Montane Shrub/Willow/ Tundra/Páramo	Alonzo et al. [73], Cunliffe et al. [74], Han et al. [75], Orndahl et al. [49], Orndahl et al. [50], Osorio-Castiblanco [76], Poley et al. [77], Putkiranta et al. [78], Talucci et al. [79], Villoslada et al. [80]
Temperate Grassland or Shrubland	Chen et al. [81], Hartley et al. [82], Madsen et al. [83]
Temperate Coniferous Forest	Herzog et al. [84], Shrestha et al. [85]
Temperate Woodland	Jucker et al. [86], Slavskiy et al. [87]
Riparian Willows/Shrubs	Husson et al. [88]
Mangroves	Li et al. [89], Navarro et al. [90]
Experimental Plantings	Combs et al. [91], Elshikha et al. [92], Tamiminia et al. [93], Tao et al. [94], Zhang et al. [95]
Park/Urban Planting	Cheng et al. [96]
Global Plant Communities	Brede et al. [47], Cunliffe et al. [48]

4.2.2. Aboveground Biomass UAV Mission Planning

One of the goals of the systematic literature review was to summarize the most common UAV mission-planning parameters, sensor types, ground truthing methods, and data processing strategies to inform our current understanding of how available technology influences models of aboveground biomass in shrubland and savanna ecosystems. A wide variety of mission-planning parameters and types of UAV platforms and sensors were used to estimate aboveground biomass in shrublands and savannas. Table 6 summarizes the usage of different aerial platforms and sensors used in the studies reviewed. RGB sensors were by far the most accessible and widely used, with both multispectral and LiDAR sensors representing the second most popular choices. Thirty percent of the studies combined two or more sensors in their workflows, with RGB and multispectral sensor combinations being the most commonly used ($n = 8$). However, 16% did not use any spectral sensors, but they used UAV-based LiDAR alone for estimating aboveground biomass. Table S1 shows a detailed overview of the UAV and mission-planning-related decisions used.

Table 6. Summary of the range of uncrewed aerial vehicle (UAV) equipment and mission-planning decisions used for estimating shrub/savanna aboveground biomass.

Equipment Type	Percent of Studies	Sensor Type	Percent of Studies ¹
Rotorcraft	80%	RGB	62% ($n = 31$)
Fixed wing	14%	Multispectral	34% ($n = 17$)
Various or not reported	6%	Hyperspectral	6% ($n = 3$)
		Thermal	4% ($n = 2$)
		LiDAR	30% ($n = 15$)

¹ Percentages add to more than 100% because several studies used combinations of more than one sensor type.

Mission planning involves decisions regarding the desired ground sampling distance (GSD) for spectral sensor operations. Achieving the desired ground sampling distance is a function of each sensor specification (i.e., megapixel count or resolution and focal length) and flight altitude, which is determined by factors such as vegetation height, regulatory

demands, and terrain-following capabilities of the UAV. The battery life of the sensor/aerial platform and the size of the area to sample also influence the resulting GSD. For studies that reported GSD, the range was 0.4 cm to 19 cm. For the studies that used combinations of spectral sensors, RGB was typically used to collect finer spatial resolution details, while the complementary sensor was often used at coarser spatial resolutions. Forty-eight percent of the spectral sensor studies reported the imagery collection flight pattern. Research teams were split almost evenly between the use of single grid patterns ($n = 9$) and double grid or double + grid patterns ($n = 8$). Only two of the included studies relied on manual or freehand patterns for image acquisitions [68,91].

Most studies used UAV photogrammetry for the purpose of achieving structure-from-motion (SfM) 3D point clouds. As such, forward and side overlaps between images were generally high. For the 28 studies that reported image overlap, mean forward overlap was 79% (± 1.6) and mean side overlap was 76% (± 1.8). The reporting of the use of ground control points (GCPs) and manual tie points (MTPs) was very inconsistent. Nineteen studies reported the number of GCPs and/or MTPs used during the photogrammetric processing step. The mean number of GCPs/MTPs used was 15 (± 3), but the range varied widely from 2 to 58 per plot or site, as defined by the researchers. Rotation or placement of the sensor relative to the ground position varied as well. Eight studies reported the use of nadir or near-nadir sensor position. One study reported an oblique camera position [73], and eight studies reported the use of both nadir and oblique sensor positions. Approximately half of the studies using spectral sensors did not report sensor angles ($n = 18$).

For the 15 studies that used LiDAR as their only UAV-based platform, average individual flight altitudes ranged from 40 m to 125 m AGL, with a mean of 82 m (± 6). Flight path side overlap amount for LiDAR missions varied across the studies and the sensors used. Some LiDAR sensors were co-mounted with spectral sensors, and the spectral sensor mission parameters dictated the amount of side overlap used in the mission plan. In the seven studies that reported side overlap for solo-mounted LiDAR acquisitions, the mean side overlap was 57% (± 6) with a range of 30% to 80% overlap.

4.2.3. Aboveground Biomass Data Processing Workflows

For both UAV LiDAR and digital aerial photogrammetry, to derive 3D plant or vegetation structure, several data processing steps were performed with the goal of estimating aboveground biomass in shrubland and savanna ecosystems. Only six of the included studies attempted to estimate aboveground biomass across more than one period (Table S1). The remaining 44 studies all made UAV data augmented biomass estimates within one field season, or with all data collected within a one- to two-week period. Of the six studies that estimated aboveground biomass over more than one period, only one study used UAV-acquired data across more than a single 12-month period. It is clear that little is currently known about the accuracy of aboveground biomass estimates using UAV-based LiDAR or structure derived from digital aerial photogrammetry across multiple periods in shrublands and savannas.

Several ($n = 12$) research teams used UAV photogrammetry or LiDAR to scale with satellite-based remote sensing products to determine single-point-in-time aboveground biomass estimates across broader spatial and temporal scales. Six studies used either Sentinel-1 (Radar) or Sentinel-2 data or both, four used either Landsat MSS, TM, or OLI sensor products, two used GEDI (LiDAR), one used GF-6, and two used PlanetScope data. Four of the 50 studies paired UAV-acquired data with terrestrial LiDAR or manned aircraft LiDAR acquisitions. Two studies paired their UAV data with 0.5 m spatial resolution manned aircraft photogrammetry products. Almost half of the included articles ($n = 24$) used UAV mission data as the only remote sensing product in their workflows.

When plant structural data were acquired, a variety of different algorithms and software were used to classify dense 3D point clouds from LiDAR and/or structure-from-motion (SfM) for the purpose of rasterizing classified points into digital surface models (DSMs) and digital terrain models (DTMs). Several studies used photogrammetric software for DSM and DTM generation (Table S2). Others used photogrammetry software to export 3D point clouds and then used other software (e.g., LASTools) to set project-specific classification settings. Many times, research teams used geostatistics (e.g., kriging, moving windows, and other interpolation methods) to estimate terrain characteristics where there were gaps in the point cloud due to canopy occlusion. Cloth simulation filter (CSF), progressive morphological filter (PMF) [60], manual segmentation, triangulated irregular network (TIN) filtering [97], and proprietary software algorithms were all employed (Table S2). Most of the reviewed papers did not assess the accuracy of their choice of ground classification algorithm, and no systematic review has been published that evaluates the efficacy of the various ground classification methods and their influence on canopy heights or other canopy metrics. This is currently a research gap.

Several plant structural features were evaluated for use in aboveground biomass models. The most common structural features were maximum height ($n = 19$) and mean height ($n = 16$). Other frequently measured structural features included canopy area, canopy width, and equation-based or voxel-based measures of canopy volume. Gray scale co-occurrence matrix (GLCM) textures, LiDAR point intensity metrics, and topographic metrics were occasionally used. Table S3 lists all structural and landscape metrics used in the 50 papers evaluated. While several research teams measured basal diameter of shrub stems during harvest or when collecting structural features, basal diameter was not used in modeling aboveground biomass from remotely sensed data. The research teams that collected diameter data used the values to estimate individual shrub/tree aboveground biomass in developing or applying allometric equations. Individual-level estimates of aboveground biomass were then scaled to the plot or site level. As expected, basal diameter was not used in model development since it is very difficult to retrieve accurate representations of stem basal diameter from UAV platforms for many shrub species, especially from NADIR surveys.

When plant spectral data was acquired, a common workflow procedure involved classifying vegetation into either individual species, plant functional types (PFTs), or land cover types homogenous enough so that the land cover types could be used as the unit for estimating aboveground biomass. Procedures for classifying vegetation into classes varied across the studies. Machine learning methods of classification, such as decision trees, Random Forest (RF), and neural networks (NNs), were also frequently used approaches for vegetation classification ($n = 14$) (Table S2). Object-based image analysis (image segmentation and classification) was also a frequently tested classification method ($n = 11$). Height thresholding of 3D point clouds (LiDAR or SfM) was used in four studies to differentiate vegetation types from each other before estimating aboveground biomass. Manual segmentation within point cloud visualization or GIS software or GIS, watershed segmentation algorithms, and fuzzy clustering or k-means clustering were the least reported methods. Table S2 summarizes the classification methods, statistical analyses, evaluation metrics, and best-performing models.

Spectral data alone was used to estimate aboveground biomass in several of the papers reviewed ($n = 8$). When spectral information was used in the development of models to estimate aboveground biomass, the limits of the UAV sensor drove the suite of spectral vegetation indices that were used by the researchers. Table S3 lists all the spectral and structural characteristics used across the 50 papers reviewed. Of the 135 spectral indices or spectral bands tested, the most used ($n = 18$) spectral index was the normalized difference

vegetation index (NDVI). Indices that can only be calculated when spectra are available from spectral radiometers (hyperspectral sensors) were limited to only those studies that used those sensors. For example, teams that only had RGB sensors available used most frequently the excess green vegetation index (EXG) and normalized green–red difference index (NGRD) in their models ($n = 8$). Research teams that paired ground and UAV-based measurements with satellite data also used some of the indices with short-wave infrared (SWIR) bands. SWIR spectral ranges are not available for most UAV platforms. The most used index in the suite of SWIR-based indices was the land surface water index (LSWI), with three studies using that index in their models.

4.2.4. Field Data Collection Methods for Ground Truth

Ground truth procedures for aboveground biomass estimates varied across and within the included papers. Some plant functional types and shrub/savanna species have published allometric equations useful for pairing with UAV photogrammetry. Other ecosystems do not have published allometries for the species of concern, or the existing allometries are not compatible with the features distinguishable by UAV data collection. Of the 50 studies, over half conducted direct harvest of species or PFTs ($n = 27$) (Table S2). Twenty-three studies used vegetation measurements to impute allometric equations rather than direct harvest. Four combined both harvest procedures with allometry-based biomass estimates for ground truth. When plots were directly harvested, the number and size of plots varied. The number of plots harvested ranged from 4 to 2400 across the suite of studies, with a mean of 185 (± 93) harvested plots. Ten of the 50 studies reported the number of plots/trees/shrubs that were collected during field measurements for use in allometric equations. The mean number of plots/trees/shrubs measured per study was 155 (± 79). One study augmented the seven trees they took field measurements of with allometric measurements on 46 individual trees within the terrestrial LiDAR-derived 3D point cloud. In 12 of the 50 studies, the plot size used was the size of individual distinguishable shrubs or trees within plots. Nineteen studies used systematic biomass harvests across plot sizes that ranged from 0.25 m² to 11.96 m². Thirteen studies that reported using allometric measurements to estimate biomass did not report the number of plots, trees, or shrubs sampled. Two studies used biomass estimates for plant functional types or forest types developed from other publications as the basis for their biomass estimates, a strategy that may or may not provide the level of accuracy needed to achieve modeling objectives.

4.2.5. Statistical Analyses

A variety of methods were proposed across the suite of studies examined to obtain aboveground biomass estimates at either the individual plant level (shrub or tree), the plot level, or the landscape spatial scale. Machine learning models were tested in 12 studies including: Random Forest (RF), decision trees, classification and regression trees (CARTs), artificial (ANNs), convolutional (CNNs) and backpropagation (BP) neural networks [93,96], support vector machine (SVM) and support vector regression (SVR) using SVM, and extreme gradient boosting (XGBoost) (Table S2). A variety of standard regression models were also used: simple linear regression; multiple linear regression; ordinary least squares (OLS) regression (including geographically weighted regression); generalized least squares regression; partial least square regression (PLS); stepwise linear regression; multivariate adaptive regression splines (MARSs); principal component regression (PCR); and quadratic, cubic, logarithmic, exponential and power regression models. Other statistical models used included generalized additive models (GAMs), linear mixed-effects models with and without LASSO regularization, and principal components analysis (PCA). To determine

treatment effects over time on aboveground biomass, Shrestha et al. [85] used a linear mixed-effects model with nested ANOVA.

One of the challenges the research teams faced when using multiple linear regression methods was determining how to remove or reduce the use of collinear predictor variables in their models. Several studies used Pearson correlation coefficients, variable inflation factor values (VIF), and/or stepwise regression to select and prune potential predictor variables down to five or six independent variables for use in the multiple variable regression models. For studies that used machine learning regression techniques, the Variable Selection Using Random Forest (VSURF) algorithm, Boruta algorithm, Random Forest-recursive feature elimination algorithm, and M-statistic were solutions used to reduce the potential predictor variables in the models [60,78,80,89]. Many of the studies used leave-one-out cross-validation (LOOCV) or k-fold cross-validation to evaluate the fit of the aboveground biomass models. Model selection was typically conducted through review of possible models by looking at root mean square error (RMSE), R^2 values, adjusted R^2 values, or lowest Akaike Information Criterion (AIC) scores. Nine of the reviewed studies did not evaluate their model performance for either aboveground biomass or carbon stocks.

4.2.6. Best-Performing Aboveground Biomass Models

To evaluate model performance for estimating aboveground biomass using UAV platforms, we grouped studies into those that used structural predictor variables, those that used spectral predictor variables or vegetation indices (VIs), and those that combined structural and spectral/VI predictor variables in their models (Table 7). A fourth type of model combined structural or spectral predictor variables with topographic, evapotranspiration, soil moisture, or other predictor variables. Model performance values were reported for the best models (highest R^2 values or adjusted R^2 values) provided by each study (Table S2). Most research teams selected models that contained at least one, if not multiple, structural features in their top-performing models ($n = 31$). However, seven papers did not evaluate their model performance. Of the 31 papers that selected structural metrics alone in their top model, only seven studies considered spectral information in their potential models. Seventeen additional studies in the “structural group” collected UAV-based spectral information and could have used that information in their model development if it had been available. Eight studies used UAV-based LiDAR sensors that did not collect any spectral data.

Table 7. Summary of AGB model types and mean model performance by coefficient of determination.

Model Type	Percent of Studies	Model Performance Range ¹	Mean Model Performance ¹	One-Way ANOVA p -Value ²
Structural	62%	0.28–0.99	0.78 (± 0.03), $n = 24$	0.8512
Spectral or VI	14%	0.55–0.95	0.73 (± 0.05), $n = 7$	0.9589
Structural and Spectral	16%	0.07–0.90	0.71 (± 0.08), $n = 8$	0.6312
Other	8%	0.51–0.60	0.55, $n = 2$	

¹ Reported R^2 or Adjusted R^2 values. ² Reported p -values are from Tukey HSD pairwise comparisons from one-way ANOVA in the following order, structural:spectral, spectral:structural & spectral, and structural:structural & spectral.

Seven studies found spectral vegetative properties alone to be the best predictors of aboveground biomass. Two studies tested vegetal structure in various models but found better model performance when omitting structural information [77,93]. The other five studies did not include structural information in the models they tested, even though they could have used SfM-derived canopy structure information. Seven of the 50 studies found that combinations of structural and spectral information were included in their top biomass model(s). These more complex models did not result in better model performance, as shown by the range and means of R^2 values reported in Table 7. As an example, Orndahl

et al. [50] reported variations in the ability of their complex model to explain variance in the data, with low performance for evergreen shrubs ($R^2 = 0.07$), while deciduous shrub models performed better ($R^2 = 0.41$) in the same study. We evaluated the effects of statistical methods (RF, XGBOOST, simple linear regression, and multiple linear regression) on model performance. No differences were found on the coefficient of determination across any of the statistical methods used in the evaluated papers ($n = 39$) using the same ANOVA and Tukey HSD pairwise comparison methods as above.

The UNFCCC's REDD+ guidelines aim for a maximum 10 percent uncertainty level for carbon stock estimates [98]. We evaluated the 15 studies that achieved an R^2 value of 0.85 or higher to examine which study characteristics may have resulted in better model fits for aboveground biomass (Table 8). The 15 studies that developed models within an acceptable range of uncertainty can attribute their success to having very few life forms or a single species to model. More complex vegetation community models tended to result in biomass estimates with higher levels of uncertainty, especially those that contained several different life forms within the plant community type or forest type (herbaceous, shrubs, and trees). Of the 15 studies with the lowest uncertainty in their models, five used machine learning algorithms, while nine used simple or multiple regression models. One study found a power regression equation more helpful than linear regression for modeling aboveground biomass. Lastly, one of the top-performing models involved using UAV-derived metrics in place of field metrics for individual tree allometry equations to obtain aboveground biomass estimates. Ten of the 15 studies used structural predictor variables only, two used spectrally derived predictor variables, and three used combinations of structural and spectral predictor variables to estimate aboveground biomass.

Table 8. Summary of top-performing AGB models (R^2 of 0.85 or higher), modeling method, model performance, and predictor variables used in the models.

Study	Best Model Method	Model Performance ¹	Vegetation Type	Best Model Predictor Variables ²
Alonzo et al. [73]	Multiple linear regression	0.88	Tall shrubs	Mean height of returns between 0.1 and 5 m, mean height of returns/median height of returns, and % canopy pixels between 1 and 4 m
Cheng et al. [96]	RF	0.85	City park shrubs and trees	NDRE, RECI, WDRVI, NDVI, RVI, GNDVI, GLCM mean, entropy, and correlation
Cunliffe et al. [74]	Simple linear model	0.90	Willow	SfM canopy height
Cunliffe et al. [48]	Simple linear model	0.91 and 0.99	Succulents and ferns	SfM mean canopy height (shrubs only had an R^2 of 0.59 and trees 0.71)
Ding et al. [54]	Power function regression model	0.897	Desert shrubs	Shrub coverage estimate
Hartley et al. [82]	Multiple linear regression	0.99	Gorse shrublands	Cumulative percentage of returns below the 90th height decile, kurtosis of height distribution of returns, percentage of voxels within the total voxelized area that contain at least one return for voxels of 5 cm
Herzog et al. [84]	Simple linear regression	0.95–0.99	Sparkleberry	Shrub coverage estimate
Leite et al. [65]	RF	0.88	Tree fuels (Cerrado)	Relative height at 98th percentile, plant area index, canopy cover fraction, foliage height diversity index
Mao et al. [56]	Simple linear regression	0.749–0.919	Desert shrubs	Canopy volume (one species 0.749, the other species 0.919)
Mao et al. [58]	Multiple linear regression	0.929	Desert shrubs	Entropy of GLCM, canopy volume, and color intensity index
Navarro et al. [90]	UAV derived allometry values	0.917–0.932	Mangrove	Maximum height, canopy diameter (all trees and top canopy only)
Sun et al. [60]	RF	0.85 (training), 0.84 (testing)	Single desert shrub species	Crown area, crown perimeter, long-to-short crown dimension ratio, crown height variation, density variable
Tamiminia et al. [93]	RF	0.95	Willow	DVI, GLI, NDVI, Red, and NIR, Green, VARI, CVI, RedEdge, NGRDI, SAVI, CI green, CI rededge, WDRVI, NDRE, RVI, Blue EXG

Table 8. Cont.

Study	Best Model Method	Model Performance ¹	Vegetation Type	Best Model Predictor Variables ²
Villoslada et al. [80]	XGBoost	0.90	Willow	For total woody AGB (canopy height NDVI, GRVI, CVI, DIS, Datt4, GRDI)
Zhao et al. [62]	Multiple linear regression	0.86	Single desert shrub species	Contrast-SUM, volume, thickness, RVI-SUM, Major axis, DVI-Range, Mean_Range, 50thPercentile_height, RVI-Max, Variance-sd

¹ Reported R² or Adjusted R² values. ² For definitions of acronyms for structural and spectral predictor variables, refer to Table S2.

5. Discussion, Knowledge Gaps, and Future Directions

5.1. Discussion of Ecosystem Representation in the Remote Sensing Literature

In evaluating the first research objective of this paper, it is important to point out that a limited number of journals were used in the analysis, subsequently limiting the breadth of our findings across the research body. Given the journals selected for this portion of the analysis, it was not surprising that tundra, savanna, woodland, desert, rangeland, and other dryland terms were associated with the least studied ecosystem groups in the remote sensing literature [8,99]. A lack of research interest in dry woodlands was identified by Schimel [8]. Our work agrees with Martin et al. [100], who suggested that temperate ecosystems, especially in wealthy countries, are overrepresented in ecological research, and with Schimel [8], who suggested that drylands are underrepresented in remote sensing research. It is possible that our findings for this first research objective could be different than those of future research that examines this question across not only remote sensing-specific journals but also journals focused on arid and semi-arid ecosystems.

Several factors may be contributing to the underrepresentation of tundra, dryland, and savanna ecosystems in the remote sensing literature. Operational temperature limits of many UAVs may be contributing to research gaps in the coldest areas of species distributions, including within Tundra ecosystems [101]. The difficulty of accessing tundra sites has also been implicated as causing underrepresentation [102]. The logistics of moving qualified researchers to dryland areas across the globe can hinder the amount and quality of research in rangelands and drylands of the world. The remote nature of the many villages and communities that dot the expanses of dry shrublands and savannas is also likely to reduce research interest and stretch limited funding resources. Piccolo et al. [103] found that proximity to a university location was the strongest predictor of study site location for reptile research in Australia. Costs associated with the deployment of UAV pilots and ground truthing teams are likely to reinforce this finding even within UAV remote sensing papers. Guerra et al. [104] found that drylands receiving less than 502 mm of precipitation annually and shrublands were underrepresented in studies of soil biodiversity and ecosystem function compared to their respective global land cover. Parker et al. [105] also documented gaps in research within the warmest ranges of potential distribution shifts for species-specific ranges. Language barriers and research expenses tend to limit ecological data collection in remote locales more than in areas of closer proximity to universities [105].

Geographical and research cost issues were not the only factors limiting research in drylands and savannas. Political and government support for research was influential in allowing overrepresentation of research in California and South Africa; however, areas lacking political and government support are frequently underrepresented [105]. Our systematic literature review agrees with Parker et al. [105], who suggested that areas with governments politically friendly to UAV research were overrepresented in UAV studies of aboveground biomass (U.S. and China making up 52% of the included studies). We

also found that wealthier nations were overrepresented in the UAV-based aboveground biomass literature.

UAV research supporting REDD+-based initiatives to quantify changes in carbon stocks in developing nations is not yet happening at a pace that would reduce the underrepresentation of research in these nations. Substantial geographical gaps exist within UAV-based quantification of aboveground biomass in terrestrial systems, indicating representation within shrubland and savanna ecosystems is lacking in a wide enough area of their global distributions to adequately quantify the contributions of these systems to global carbon stocks. It is possible that the establishment of research outposts in geographically underrepresented areas and investments into university and government policies allowing UAVs for ecological investigations could reduce the level of underrepresentation and address key geographical and ecosystem group research gaps more effectively.

5.2. Discussion of UAV Methodologies for Estimating Aboveground Biomass

5.2.1. Temporal Frequency of Data Collection

The results of this review have highlighted a number of key knowledge gaps (Table 9). A major gap identified in this review is the limited temporal scope of most UAV-based AGB studies. Nearly all studies collected data within a single growing season, limiting the understanding of interannual variability. In shrub-dominated and savanna ecosystems, where biomass can fluctuate substantially due to drought, phenology, or disturbance, a single acquisition may not represent typical biomass conditions. This limitation is particularly important when UAV-derived models are scaled with multi-year satellite datasets. Without temporal alignment, scaled AGB estimates may be biased if extreme wet or dry years are not represented. Similar temporal gaps have been reported in soil biodiversity research [104] and UAV grassland studies [25], suggesting a broader issue across ecological remote sensing. Addressing this gap would improve estimates of shrub and savanna carbon stocks and strengthen their use in carbon accounting and fuels assessments.

Table 9. Key findings and knowledge gaps identified from the systematic literature review of UAV estimation of aboveground biomass in shrublands and savannas.

Key Findings	Knowledge Gaps	Recommendations for Future Research
With only 50 published peer-reviewed journals using UAV systems to estimate AGB, no clear workflow exists that reduces uncertainty in estimates to less than 10%.	Improved workflow testing across different vegetation characteristics is needed	Global cooperation is needed to conduct studies similar to Cunliffe et al. [48] for the purposes of testing workflows that dramatically decrease uncertainty in shrubland and savanna ecosystems.
Allometry models do not exist within the uncertainty threshold of 10% for many plant species or plant functional groups in shrubland/savanna systems.	Researchers are having to harvest vegetation at considerable time and expense to conduct AGB research	Widespread allometry studies are needed at the species level across many shrublands and savannas in order to reduce uncertainty in AGB estimates to 10% or less.
UAV is the most widely used acronym for drone-based remote sensing.	There is a need to standardize some of the language used to describe UAV-based research to improve literature searches and definitions	Petitions by professional societies to remote sensing journals for standardization of acronyms and drone-based remote sensing terminology would improve the searchability of the literature.
Global carbon stock estimation has been spatially biased and likely does not represent the true diversity of carbon stocks in shrubland and savanna ecosystems.	Need to improve understanding of shrubland and savanna contributions to global carbon stocks	Improve locations and spatial sampling strategies for funding research in global carbon stock quantification.
Most UAV research does not consider time scales of management for AGB estimates.	There are no standardized procedures yet in place for monitoring changes in AGB over two or more time periods using UAVs	Improved reproducibility and replicability of AGB estimates is needed for comparing estimates across time scales.

5.2.2. Mission Planning and Reporting

While reviewing mission-planning parameters across studies, we found inconsistent reporting of key methodological details. The reporting of mission-specific information was inconsistent, especially in the reporting of ground control and georeferencing procedures, but also mission decisions such as side overlap for LiDAR missions, front and side overlap for spectral sensor missions, and ground sampling distance (GSD) achieved. Considerable model uncertainty could arise due to poor ground control procedures and could limit the scalability of UAV datasets with satellite acquisitions. Although Bazzo et al. [25] found no differences in aboveground biomass estimates in grasslands across various flight altitudes or flight overlap amounts, we recommend that UAV researchers aim for some standardization of mission-planning reports to facilitate future meta-analyses and systematic literature reviews. Standardization and professionalism in data reporting could be adopted by journal editors, or standardized UAV metadata attached as supplemental reports could serve to advance the science of UAV platform studies in the future.

Another issue that was identified through the lack of standardized mission reporting is that there is no handbook or widely accepted methodology yet developed for UAV-augmented dryland vegetation characteristic estimation and monitoring [18,106]. This is not surprising given the recent adoption of these technologies within the research community (Figure 3). However, UAV technologies have shown value in scaling aboveground biomass estimates [55,75,81,94] and for vegetation monitoring [107]. We recommend that to address this gap, researchers within the dryland biomass estimation and vegetation monitoring community come together for annual conferences with key management agencies to discuss the state of the science, seek funding for a multi-nation working group to develop a handbook for UAV-augmented vegetation monitoring, and create a pathway document that non-government organizations (NGOs) and governmental agencies can use to adopt wide-scale UAV-augmented vegetation management and aboveground biomass estimation protocols. Ultimately, the goal in the U.S., where the authors are located, should be the publication of several multi-agency technical reference manuals for riparian and upland vegetation monitoring using UAV-based data in conjunction with accepted field sampling. It is likely that these locally collected data sources could then be made available to research groups to perform the scaling of these data with appropriate satellite-based products.

5.2.3. Effectiveness of Aboveground Biomass Models

We found no clear advantage of any single modeling approach for estimating AGB in shrublands and savanna systems. Similar to the findings of Poley and McDermid [18], structural-based, spectral-based, or combined structural-spectral aboveground biomass models were not statistically different from each other in effectiveness. Model performance varied dramatically ($R^2 = 0.07\text{--}0.99$), suggesting ecosystem-specific factors may be more important than workflow decisions alone. We strongly recommend that research teams collect both structural and spectral data using UAV platforms in each new ecosystem they attempt to estimate aboveground biomass and carbon stocks within. We summarized the explanations of many of the causes of large RMSE variability or low R^2 values given by researchers in the included papers (Table 10). It is important to note that 61% of the 39 studies reporting a coefficient of determination were most successful with structural predictor variables. Also, 66% of the 15 studies that achieved a 15% or less level of uncertainty used structural characteristics alone in their models. This reliance on structural data to estimate aboveground biomass for small trees and shrubs is not surprising, as structural data has been the primary source of information for traditional allometric models [29,30,32]. Structural features such as canopy height, width, area, and volume were all important predictor

variables of individual plant aboveground biomass estimates and would be wise additions as predictor variables to any shrubland or savanna model of aboveground biomass.

Table 10. The explanations given by authors concerning the challenges they experienced in estimating aboveground biomass and possible reasons for the high RMSE values or low R^2 values.

Challenges	Recommendations for Overcoming Challenges	Citations
• PPK or RTK needed for satellite fusion, limited distances from roads/ground control options, issues with controlling location of field data compared to UAV data.	• Clearings, roads, or RTK units needed to overcome ground control in dense or multi-layered canopies to allow multitemporal registration and georeferencing with satellite data.	Brede et al. [47]
• Increased point cloud density relative to AGB model performance needs to be tested, reduced ability to return DBH with UAV-mounted systems compared to TLS.	• Develop allometric scaling models that allow for biomass estimation using tree crown and height metrics rather than DBH. Improve validation across different ecosystems.	Brede et al. [47], Levick et al. [66]
• Species-specific detection and classification could improve AGB models.	• Need hyperspectral data or computer vision models to properly classify all species beyond functional groups prior to biomass modelling.	Alonzo et al. [73], Brede et al. [47]
• Classification errors, CHM errors and AGB RMSE values were greater when vegetation was less abundant, when canopies were less distinct, or when vegetation was shorter statured.	• Improve spectral or spatial resolution to more effectively characterize less distinct or less abundant vegetation types. Improve ground classification to reduce uncertainty in CHM.	Orndahl et al. [49], Matyukira and Mhangara [67]
• Species or plant functional types with more physiognomic diversity were more challenging to model.	• Improved allometric models, higher resolution structural data.	Orndahl et al. [49], Poley and McDermid [18]

A key limitation of UAV-based AGB estimation is reliance on allometric models that often require stem basal diameter, an attribute difficult to measure remotely. Conti et al. [29] achieved $R^2 = 0.93$ when shrub basal diameter was included, but model uncertainty increased when it was excluded. Until UAV-compatible, species-specific allometries achieve $\leq 10\%$ uncertainty, combining structural and spectral predictors remains advisable.

Another potential source of error in remotely sensed aboveground biomass models for dryland shrubs is the seasonal or daily variation in plant leaf characteristics due to para-heliotropism, drought, or seasonally induced dropping of ephemeral leaves [108,109]. These rapid changes in leaf characteristics, if not considered carefully, could cause additional error if harvest activities do not occur in close temporal proximity to the collection of UAV-based imagery or LiDAR data. Other sources of aboveground biomass model error, as described by Tian et al. [21], include field sampling error, errors in statistical model structure, errors in model parameters, and sensor-based errors. Canopy height errors can occur due to sensor-related issues and the choice or type of ground classification algorithm [21]. Poley et al. [77] found that CHM estimates were not as useful as accumulated VI metrics for estimating biomass in tundra shrublands. Gillan et al. [110] found that SfM-based CHM estimates underpredicted plant heights by up to 45%. Dense vegetation can also cause difficulty in separating DTM points from DSM points in SfM-derived point clouds [77]. Overall, ecosys-

tem characteristics and allometric constraints appear to influence aboveground biomass model performance more strongly than specific statistical or workflow decisions.

5.2.4. Insights from UAV/Satellite Scaling Studies

While evaluation of the use of UAV data for scaling with satellite data was not one of our main research goals, several of the systematically reviewed studies did use UAV-acquired data to build satellite-based models of aboveground biomass. UAV sensor data are increasingly used to calibrate and validate satellite-based AGB models, and this trend is likely to continue. When scaling UAV-based aboveground biomass estimates with spectral satellite data, spectral predictor variables were important in all but two studies that evaluated spectral and structural UAV information [55,75,81,94]. Two studies modeled UAV-based AGB estimates and scaled them with GEDI data. Leite et al. [65] found good model performance for tree and total fuel models ($R^2 = 0.88$ and 0.71 , respectively); however, model performance was less than desired for herbaceous and shrub vegetation ($R^2 = 0.46$ and 0.15 , respectively), which might be expected due to the uncertainty present in GEDI-based canopy height models for short-statured plants and the use of a species-agnostic shrub allometric equation for AGB estimation. Similar results were reported by Malambo and Popescu [111] in their estimations of canopy height for deserts and xeric shrublands ($R^2 = 0.49$) using ICESat-2 and other datasets. Model performance using ICESat-2 was lowest in sparsely or heterogeneously vegetated deserts and chaparral forests; however, it is still important to point out that the best-performing satellite-based models contained both structural and spectral datasets [111]. Additional research is warranted to further develop workflows and procedures for scaling UAV-acquired datasets with newer fine-scaled spectral satellite products [112], products from forthcoming BIOMASS and NISAR missions [113], and geographically large aerial photogrammetry missions paired with similar extent LiDAR missions [114].

One of the current limitations globally to using UAV imagery or structural information (LiDAR or SfM) to scale plot-level estimates with satellite-based products is the accuracy of the ground control and GNSS locations [21,47]. Brede et al. [47] point out that post-processing kinematic (PPK) methods for UAV-based forms of data collection can be helpful for joining ground-based data and surveys to satellite pixels. Tian et al. [21] reference the limitation that, without highly accurate GNSS receivers, it is possible to have field plot and UAV plot mismatches with satellite-based data. Developing countries may not have adequate access to highly accurate GNSS receivers during UAV missions and could benefit from more cross-collaboration with research teams that have this equipment.

5.2.5. Emerging Technologies and Future Directions

Emerging technologies and computing developments will likely change future workflows and, hopefully, the accuracy of remotely sensed estimates of aboveground biomass. While hyperspectral sensors on UAVs were used in only three of the 50 papers reviewed, the currently prohibitive costs of UAV-mounted hyperspectral sensors are likely to decrease in the years to come. Future increased use of hyperspectral sensors should improve classification accuracy for species in complex vegetation types such as shrublands and multiple canopy layer savanna systems [24]. Classification error is one of the many sources of uncertainty or error in aboveground biomass estimates [18,115]. Aerial hyperspectral sensors, combined with aerial LiDAR, substantially advanced 3D monitoring of terrestrial ecosystems [115]. As the costs of UAV-mounted hyperspectral sensors with co-mounted LiDAR systems drop, new datasets and discoveries will be made about species-specific aboveground biomass changes and community dynamics. In this review, many research

groups were only able to model plant functional groups due to the difficulty of classifying individual species. This is less expected to be a challenge with hyperspectral UAV missions.

In this review, only four papers used a neural network, a convolutional neural network, or other computer vision technique to classify vegetation prior to applying their biomass models. The use of computer vision and other deep learning techniques to reduce classification error and build biomass estimation models is expected to increase in the near future. Zhang et al. [116] caution that appropriate ground-based biomass measurements will be needed to form validation datasets for expanding deep learning models for aboveground biomass estimation across spatiotemporal scales.

Emerging hyperspectral LiDAR systems may further improve biomass estimation by integrating structural and chlorophyll-sensitive spectral information [117,118]. These systems could one day augment finer-scale UAV-based sensor information. Current implementations of hyperspectral LiDAR remain largely experimental and simulation-based, and their operational feasibility in large-area shrub and savanna systems remains to be demonstrated.

6. Conclusions

This manuscript provides a comprehensive review of the most relevant papers in the field of UAV-based estimation of aboveground biomass in shrubland and multi-canopy savanna ecosystems. There are several factors that affect the performance of the aboveground biomass estimation. Our findings are summarized as follows:

- Hyperspectral sensors were underrepresented in the published datasets (<7% of the reviewed papers).
- We found no consistent UAV-based sensor combinations, platforms, or workflows that resulted in improved estimates of aboveground biomass.
- Structural data (from CHM) was useful in many of the best-performing models.
- Building models and estimates of aboveground biomass appears to increase in difficulty as the diversity of physiognomic forms increases.

Our recommendations for scientists studying remote sensing of aboveground biomass estimation are based on our key findings (Table 9) and the challenges identified through this review process (Table 10). We provide the following recommendations for improving aboveground biomass estimation using UAVs:

- (1) Development of a database linking shrubland and savanna plant traits to allometric equations of aboveground biomass, along with further development of species-specific allometric models using plant traits easily measured both in the field and with UAV-mounted sensors;
- (2) Additional research into UAV-mounted sensor system workflow development could improve UAV-based sensory system scaling with satellite-based remote sensing products;
- (3) Further research into the application of multitemporal UAV-acquired datasets is also needed to temporally capture ecosystem changes;
- (4) Research and development investments are needed to manufacture low-cost co-aligned multispectral (or hyperspectral), RGB, and LiDAR sensors for mounting on UAVs, as current costs could be contributing to the underrepresentation of research in less wealthy nations;
- (5) Universities should invest in engaging lawmakers and regulators in countries with strict or limiting UAV policies to allow policy flexibility for ecological research purposes, or when barriers are insurmountable, they should invest in aerial photogrammetry or high spatial resolution satellite imagery to improve scaling of ground-based aboveground biomass estimates;

- (6) Researchers and land managers should attend UAV-based vegetation monitoring conferences together, engage in collaborative efforts across institutions, similar to Cunliff et al. [48], collaboratively develop UAV-assisted vegetation monitoring manuals, and foster sharing of expertise and research equipment, such as high-end GNSS receivers, to reduce uncertainty in aboveground biomass models while increasing representation of research in shrubland and savanna ecosystems outside the U.S. and China.

This is a rapidly expanding area of research, and UAV-acquired datasets have demonstrated value in reducing uncertainty and scaling estimates of aboveground biomass across large landscapes. It is our hope that the findings and recommendations presented here can facilitate advancement of workflows, technologies, and collaborations in this exciting area of research.

Supplementary Materials: The following supporting information can be downloaded at: <https://www.mdpi.com/article/10.3390/rs18060942/s1>, Table S1: Study design and uncrewed aerial vehicle (UAV) mission design decisions for each of the 50 papers identified following the PRISMA systematic literature review process. Table S2: Data processing steps for LiDAR and SfM structural data, statistical frameworks, and top model predictor variables for each of the 50 papers identified following the PRISMA systematic literature review process. NR = Not reported. Table S3: Systematic literature review results listing all tested predictor variables used in models for AGB estimation.

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Data Availability Statement: The search strategy, including full database query strings, is available in Table 2. All data extracted from included studies are available in Supplementary File S1.

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Abbreviations

The following abbreviations are used in this manuscript:

3D	Three-dimensional
AGB	Aboveground biomass
AGL	Aboveground level
ANN	Artificial neural network
CA	Crown area
CART	Classification and regression tree

CHM	Canopy height model
CNN	Convolutional neural network
CFS	Cloth simulation filter
DBH	Diameter breast height
DGH	Diameter ground height
DRC	Diameter root collar
DSM	Digital surface model
DTM	Digital terrain model
GCP	Ground control point
GEDI	Global Ecosystem Dynamics Investigation
GIS	Geographic Information System
GNSS	Global Navigation Satellite System
GSD	Ground sampling distance
HSD	Honestly Significant Difference
ICESat-2	Ice, cloud and land elevation satellite-2
ISPRS	International Society for Photogrammetry and Remote Sensing
Landsat MSS	Multispectral scanner
Landsat TM	Thematic mapper
Landsat OLI	Operational land imager
LiDAR	Light detection and ranging
LR	Linear regression
ML	Machine learning
MLR	Multiple linear regression
MTP	Manual tie point
NGO	Non-governmental organization
NISAR	NASA-ISRO Synthetic Aperture Radar
OBIA	Object-based image analysis
OLS	Ordinary least squares
PCA	Principle components analysis
PFT	Plant functional type
PMF	Progressive morphological filter
PPK	Post-processing kinematic
PRISMA	Preferred Reporting Items for Systematic reviews and Meta-Analyses
REDD+	Reduced Emissions from Deforestation and Forest Degradation plus role of forest management for the enhancement of carbon stocks
RF	Random Forest
RGB	Red, green, blue
RMSE	Root mean square error
SfM	Structure-from-motion
SVM	Support vector machine
TIN	Triangulated irregular network
TLS	Terrestrial laser scanner
UAV	Uncrewed aerial vehicle
UNFCCC	United Nations Framework Convention on Climate Change
YOLO	You Only Look Once

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